

Received: 19-Apr-2024

1st Revision: 24-May-2024

2nd Revision: 08-Jul-2024

Accepted: 19-Aug-2024

Citation: Zhang X, Gao LL, Luo Y, et al. (2024) Finer topographic data improves distribution modeling of *Picea crassifolia* in the northern Qilian Mountains. Journal of Mountain Science 21(). <https://doi.org/10.1007/s11629-024-8851-1>

Finer topographic data improves distribution modeling of *Picea crassifolia* in the northern Qilian Mountains

ZHANG Xiang ¹ <https://orcid.org/0009-0002-1958-3288>; e-mail: 220220947650@lzu.edu.cn

GAO Linlin ^{1,2*} <https://orcid.org/0000-0003-1805-5440>; e-mail: gaoll@lzu.edu.cn

LUO Yu ¹ <https://orcid.org/0009-0003-4129-7752>; e-mail: luoyu2023@lzu.edu.cn

YUAN Yiyun ¹ <https://orcid.org/0009-0003-5574-0428>; e-mail: 220220949680@lzu.edu.cn

MA Baolong ¹ <https://orcid.org/0009-0004-9338-0846>; e-mail: mabl2023@lzu.edu.cn

DENG Yang ^{1,2*} <https://orcid.org/0000-0002-0473-447X>; e-mail: dengy@lzu.edu.cn

*Corresponding author

¹ MOE Key Laboratory of Western China's Environmental Systems, College of Earth Environmental Sciences, Lanzhou University, Lanzhou 730000, China

² Academy of Plateau Science and Sustainability, Qinghai Normal University, Xining 810008, China

Abstract: The Qilian Mountains, a national key ecological function zone in Western China, play a pivotal role in ecosystem services. However, the distribution of its dominant tree species, *Picea crassifolia* (Qinghai spruce), has decreased dramatically in the past decades due to climate change and human activity, which may have influenced its ecological functions. To restore its ecological functions, reasonable reforestation is key. Many previous efforts have predicted the potential distribution of *Picea crassifolia*, which provides guidance on regional reforestation policy. However, all of them were performed at low spatial resolution, thus ignoring the natural characteristics of the patchy distribution of *Picea crassifolia*. Here, we modeled the distribution of *Picea crassifolia* with species distribution models at high spatial resolutions. For many models, the area under

the receiver operating characteristic curve (AUC) is larger than 0.9, suggesting their excellent precision. The AUC of models at 30m is higher than that of models at 90m, and the current potential distribution of *Picea crassifolia* is more closely aligned with its actual distribution at 30m, demonstrating that finer data resolution improves model performance. Besides, for models at 90m resolution, annual precipitation (Bio12) played the paramount influence on the distribution of *Picea crassifolia*, while the aspect became the most important one at 30m, indicating the crucial role of finer topographic data in modeling species with patchy distribution. The current distribution of *Picea crassifolia* was concentrated in the northern and central of the study area, and this pattern will be maintained under future scenarios, although some habitat loss in the central parts and gain in the eastern regions is expected owing to increasing temperatures and precipitation. Our findings can guide protective and restoration strategies for the Qilian Mountains, which would benefit regional ecological balance.

Keywords: Species distribution modeling; *Picea crassifolia*; High resolution topographic data; Climate change; The Qilian Mountains Nature Reserve

1 Introduction

The Qilian Mountains, located on the northeastern margin of the Qinghai-Tibetan Plateau, is a national key ecological function zone in Western China (Bai et al. 2023; Zuo et al. 2022). Local vegetation status is crucial to the ecologically safe and sustainable development of the national ecological function zone. However, many pressures such as climate change, have threatened the ecosystem of the Qilian Mountains (Coumou and Rahmstorf 2012; Thackeray et al. 2016; Diffenbaugh et al. 2018), especially the dominant tree species, *Picea crassifolia* (Qinghai spruce), leading to serious threat to its distribution and local ecological balance (Yang et al. 2020). Therefore, to make scientifically sound ecological protection and restoration policies to enhance the Qilian Mountains' ecological function, assessing the potential distribution of *Picea crassifolia* at present and in the future is urgently needed.

Species Distribution Models (SDMs) are quantitative models rooted in niche theory, commonly correlating species presence across multiple locations with relevant environmental variables to explore species' ecological tolerance (Booth et al. 2014; Elith and Leathwick 2009; Guisan and Zimmermann 2000). In 1984, the BIOCLIM program was launched in Australia, marking a milestone in the development of species distribution modeling. At the same time, the climate interpolation methods developed for BIOCLIM were used to build the WorldClim database (Hijmans et al. 2005), which is now one of the most popular sources of climate data for SDM studies, further advancing the development of this field. To date, SDMs have widespread applications, especially in the forestry field (Booth and McMurtrie 1988; Booth 2024; Busby 1988). They are frequently used to predict species' potential habitat ranges in space or time, offering a practical framework for identifying and evaluating habitat suitability (Araújo and Peterson 2012; Phillips et al. 2006). Moreover, SDMs can elucidate species' response mechanisms to environmental change, aiding in assessing species endangerment levels and informing conservation priorities (Guisan 2017; Puchałka et al. 2023; Mahmoodi et al. 2023). In recent years, SDMs have undergone improvements and developments (Oliveira et al. 2021; Murphy and Smith 2021). The software packages and environmental variables for SDMs are becoming growing rich. Notably, the influence of fine-grained variables and microclimate on model simulations were a major focus of related research (Austin and Van Niel 2011; Booth 2018; Maclean and Early 2023). Indeed, interpolation has been shown to better simulate the actual microclimates of species' distributions, thereby providing a good way to study the microclimates effects on SDM (Bramer et al. 2018).

Meanwhile, increasing numbers of studies have used SDMs for assessing, modeling, predicting, or mapping the distributions of *Picea crassifolia* and explored its response to the environment in and around the Qilian Mountains. For example, Cao et al. (2019) applied the Maxent model to simulate *Picea crassifolia* distribution in northwestern China under three climate change scenarios. Based on species distribution models, Xu et al. (2011) and Tu et al. (2022) depicted the potential distribution of *Picea crassifolia* in the Qilian Mountains national reserve under current conditions. However, previous studies were usually performed with smaller amounts of data and at low spatial resolution. Owing to the wide distribution of *Picea crassifolia* in the Qilian Mountains, a small number of samples may be not sufficient to represent the entire species' characteristics (Chang et al. 2014). Besides, *Picea crassifolia* is patchily distributed, thus coarse topography data may not describe the influence of topography on *Picea crassifolia* distribution (Zhang et al. 2011).

Here, we used a large number of *Picea crassifolia* occurrence data in the Qilian Mountains Nature Reserve, and applied SDMs and high-resolution topographic data to predict its current and future distribution. The objectives of this study are (1) to test whether the finer topography data improve model performance; (2) to identify

the uppermost predictors influencing the distribution of *Picea crassifolia*; and (3) to explore the current and future potential space distribution of *Picea crassifolia* in the Qilian Mountains Nature Reserve. Overall, the findings of this study would benefit the restoration and development of *Picea crassifolia* in the Qilian Mountains Nature Reserve and local ecological balance.

2 Materials and Methods

2.1 Study area

The Qilian Mountain National Reserve extends from 36°30'-39°41' N to 97°23'-103°46' E, which is situated at the confluence of the Qinghai-Tibet, Mongolia, and Loess plateaus. It belongs to the northern Qilian Mountains, with a total area of 2.653×10^6 km² (Fig. 1). Characterized by complex topography and large altitude gradient, the area exhibits a typical plateau continental climate, with an average annual temperature of 6°C and precipitation between 300-700 mm (Liang et al. 2019). The vegetation in Qilian Mountains National Reserve has a wide variety, and is dominated by alpine meadows and forests (Chang et al. 2014). *Picea crassifolia*, growing mainly on shady and semi-shady slopes, is the most widely distributed subalpine coniferous forest in the study area, as well as one of the ecosystem-building tree species. Thus, studies on this dominant tree species are vital to regional forest resources management and ecosystem balance.

2.2 Species occurrence records

The occurrence data of *Picea crassifolia* were derived from Qilian Mountains National Reserve forest resource inventory data for 2001, which is available from the National Forestry and Grassland Science Data Center (NFGSDC, <https://www.forestdata.cn/>). However, some coordinates of this data have a bias of hundreds of meters from their actual position. Thus, prior to using the data for analysis, we first visually match the shape of each *Picea crassifolia* patch with nearby vegetation in Google Earth Pro (version 7.3) (<https://earth.google.com>). Additionally, to reduce the geographic bias and spatial correlation, each occurrence point of *Picea crassifolia* was set in the center of the matched patchy. In total, 7260 occurrence points for *Picea crassifolia* were used for subsequent analysis.

2.3 Environmental data

Two categories of environmental data were employed as predictors in this study: DEM data and climate data. The DEM data was sourced from the "Geospatial Data Cloud" (<https://www.gscloud.cn/>), which has resolutions of 90 and 30 m. At each resolution, three topographic factors that are critical to depicting localized geographic landscapes were contained in our analyses: elevation, slope, and aspect, with the latter two derived from the DEM data with ArcGIS 10.2. Additionally, because *Picea crassifolia* tended to distribute on shady slopes, the aspect data were adjusted ($\cos(\text{aspect}/\pi \times 180)$) to have the largest value in the north and the smallest in the south.

Climate data were obtained from the WorldClim database (Hijmans et al. 2005, <https://www.worldclim.org/data/worldclim21.html>), which is the climate of 1970–2000 and has a resolution of 30s (~1 km×1 km). This dataset includes monthly temperature and precipitation, and 19 bio-climate variables (Booth et al. 2014). There might be strong spatial correlations among these bio-climate predictors. To avoid the influence of model overfitting caused by the correlation between these factors on the model (Fiore et al. 2017), the correlation coefficients within bio-climate variables were calculated by the 'correlation' package in R (Makowski et al. 2020). The factors whose correlation coefficient was over 0.8 and passed the statistical test were considered to have high collinearity (Chhogyel et al. 2020). Among these variables, we would like to choose the one which is normal

distribution, more collinearity with other same-type variables, and small collinearity with topography predictors for fully considering the influence of temperature and precipitation on spruce distribution. Further, related researches also emphasize the importance of these two predictors to the distribution of *Picea crassifolia* (e.g., Zhao et al. 2010). Therefore, annual precipitation (Bio12) and mean temperature of the warmest quarter (Bio10) were used here (Appendix 1). These variables are adequate for this study area since they represent the climatic constituents that constrain the physiology, reproduction, and life-history features of *Picea crassifolia* and are, therefore, pivotal determinants of their distribution (Feng et al. 2023). To fit the resolutions of topography, these climate raster layers with 1 km spatial resolution were resampled to the same spatial resolution as the topography raster by using the nearest neighbor interpolation method in the ArcGIS toolbox. Through this process, we generated spatial data for climate predictor variables, each with the same projection, extent, and spatial resolution, for modeling the *Picea crassifolia* in the study area.

Furthermore, to assess the future distribution of *Picea crassifolia*, the projected Bio12 and Bio10 for the period 2081–2100 were used, and four representative concentration pathways (SSPs): SSP126, SSP245, SSP370, and SSP585, were adopted. To reduce uncertainty in future climate projections, the ensemble mean of all available predictions in WorldClim was used. The topographic predictors were considered to be stable during this period. Additionally, the environmental variables for the period 2021–2040 were also used to simulate the future distribution of *Picea crassifolia* for a relatively recent period, and they were proved in Appendixes 2–4.

2.4 Species distribution modelling

To model the potential distribution of *Picea crassifolia* of currently and in the future, five commonly used techniques that implemented within the R package SSDM (Schmitt et al. 2017) were used, including Maximum Entropy (MaxEnt), Classification and Regression Trees (CTA), Generalized Linear Models (GLM), Multivariate Adaptive Regression Splines (MARS), and Generalized Additive Models (GAM). To evaluate the performance of models, the occurrence data were randomly partitioned into 70% for training and 30% for testing. Then, the area under the receiver operating characteristic curve (AUC, Bradley 1997), which is available in SSDM was used to assess the reliability of the model. A model with an AUC of 1 represents consummate discriminatory ability, and an AUC value above 0.8 indicates good model performance (Swets 1988).

To obtain the distribution of *Picea crassifolia*, a probability threshold that maximizes sensitivity and specificity was used to transform the results of probabilities into a binary map of suitable and non-suitable areas. This method has been proven to be efficient for threshold determination (Liu et al. 2005). Besides, four arbitrary categories of habitat suitability for *Picea crassifolia* were defined as: unsuitable area (0–0.1275), low suitable area (0.1275–0.5), medium suitable area (0.5–0.85), and high suitable area (0.85–1).

2.5 Statistical analysis

To further assess model accuracy, we used an unsupervised classification method called ISODATA on the Normalized Difference Vegetation Index (NDVI) (Yang et al. 2019) and the land cover in 2020 (Jie and Xin 2022), to map the true distribution of *Picea crassifolia*. In addition, to compare the influence of data resolution on model performance, the proportion of spatial overlap between the true *Picea crassifolia* distribution and the potential distribution at resolutions of 90 m and 30 m was also computed.

Additionally, two landscape indices, patch density (PD) and edge density (ED), were employed to assess the effects of climate change on habitat fragmentation. These metrics are recognized as effective measures for assessing habitat fragmentation (Wang et al. 2014), and the higher values of both PD and ED indicate increased fragmentation of the species' range.

3 Results

3.1 Model performance and variables contribution

The AUC of all models is shown in Fig. 2. The AUC of most models ranges from 0.83 to 0.94 and has a mean of 0.887, indicating good to very good performance. For models at different resolutions, the AUC of 30 m SDMs is apparently higher than that of 90 m SDMs, with an average improvement of 3.97%. The AUC of models with different modeling techniques also varied. These results indicate the influence of resolutions and modeling techniques on model performance. Among all models, the MaxEnt in 30m achieved the highest AUC of 0.94, which means it has the greatest potential to predict the actual distribution of *Picea crassifolia* in the study region.

The contributions of the predictors also differed for each resolution. Specifically, Bio12 was the most important variable in the 90m SDMs, followed by aspect, elevation, slope, and Bio10 while aspect became the most influential factor in the 30m SDMs, followed by Bio12, elevation, slope, and Bio10. The differences in variable importance at two resolutions were noticeable, with the contribution of aspect and elevation increasing remarkably from 16.0% to 27.2% and from 17.5% to 22.5%, while the contribution of Bio12 and Bio10 decreased from 36.0% to 25.7% and from 9.0% to 6.8%, respectively (Fig. 3). These results reveal that Bio12 and aspect contained larger useful information by themselves than the other variables did. Besides, topographic predictors such as aspect and elevation became more important in modeling the distribution of *Picea crassifolia* with the improvement of resolution.

Concerning the MaxEnt having the highest prediction accuracy, we employed this modeling technique for all subsequent analyses to optimize the efficiency.

3.2 Predictions with different data resolution

The distribution of *Picea crassifolia* based on classification and that predicted with MaxEnt modeling technique at 90 m and 30m resolution are shown in Fig. 4. The distribution area of *Picea crassifolia* in this study region obtained by classification was 1439.2 km², very closed to the recorded area of 1422.1 km². Thus, the distribution of *Picea crassifolia* obtained by classification was used as its actual distribution. According to the classification, *Picea crassifolia* was mainly distributed in the central and eastern parts of the study region. Both predictions generally coincided with the spatial pattern of the actual distribution of *Picea crassifolia*, however, the prediction of 90m was significantly underestimated in the eastern part of the study region. The predicted distribution of *Picea crassifolia* in 90m and 30m SDMs was 7026.67 km² and 5110.65 km², respectively, both greatly exceeding the actual area. The area predicted by 90m SDMs was 37.5% larger than the 30m SDMs. However, the area of the overlapping between the predicted spatial distribution with 30m SDM and the actual distribution of *Picea crassifolia* was 1116.64 km², which was just 5.7% lower than that of the 90m SDM. These indicate that 30m SDM is more accurate than 90m SDMs, highlighting the advantage of finer data resolution in model performance.

3.3 Dynamics in potential distribution of *Picea crassifolia* under future scenarios

To evaluate potential changes in environmentally suitable habitats for *Picea crassifolia*, we calculated the percentage change in area between the current and future scenarios. Compared to the present *Picea crassifolia* distribution, its future distribution is predicted to have a slight increment, with a minimum gain of 52.25 km² (about 1%) and a maximum gain of 110.16 km² (about 2%) under the SSP126 and SSP245 scenarios, respectively. Meanwhile, except for the SSP370 scenario, suitable area gain is more pronounced in scenarios with warmer and wetter climates.

In addition, area change for each suitable class also varied. Currently, the unsuitable, poorly suitable, moderately suitable, and highly suitable *Picea crassifolia* habitats accounted for 80.8 %, 10.2 %, 6.3 %, and 2.6 % of the study area, respectively. Under the future scenarios, the change in the highly suitable habitat was most prominent, followed by the moderately and poorly suitable habitats (Table 1). The highly and moderately suitable classes are both expected to increase. While for the poorly suitable class, its variation is diverged under different scenarios, it may slightly increase in the SSP245 and SSP370, and decrease in SSP126 and SSP585.

The distribution area transition of *Picea crassifolia* in every suitable class from 1970-2000 to 2081-2100 is shown in Table 2. At the end of the 21st century, more than 98% of the region that was categorized as unsuitable during 1970-2000 will keep unsuitable for *Picea crassifolia*. Regarding poorly and moderately suitable classes, 10%~17% of the area will transition into adjacent classes in the future. Additionally, 6%~11% of highly suitable habitats in the past will change into moderately suitable or poorly suitable classes in the future.

Spatial loss and gain of *Picea crassifolia* habitats under future scenarios are shown in Fig. 5. It was predicted that the potential distribution of *Picea crassifolia* would continue to appear in the central and western study area, with a slight decrease for the central region and increase mainly for the eastern region. The result could be attributed to some regions that currently are unsuitable for *Picea crassifolia* to live become conducive to its growth under future conditions, which will contribute to the successful colonization of these areas by *Picea crassifolia*.

4 Discussion

4.1 Model performance

Among the species distribution models (SDMs) used, the MaxEnt algorithm showed the highest precision in modeling the distribution of *Picea crassifolia*. MaxEnt is often considered to be one of the most reliable SDM techniques and is increasingly used to model species distributions and explore the influence of environmental factors on species (Ehrlén and Morris 2015; Waldock et al. 2022; Elith et al. 2010).

Our results also demonstrate a positive impact of data resolution on model performance, which is consistent with previous studies that the refinement of predictor resolution increased predictive performance (Lembrechts et al. 2023; Chauvier et al. 2022). More accurate details of studies target can be described with higher data spatial resolution (Randin et al. 2009; Dobrowski 2011; Hannah et al. 2014; Lenoir et al. 2016; Meineri and Hylander 2017). In contrast, environmental messages become fuzzier on account of more inaccuracies and growing uncertainties contained in the species response as resolution decreases (Chauvier et al. 2022; Stoklosa et al. 2014), resulting in poorer model performances.

However, the shortcomings of AUC that we used to evaluate the model precision in this study need more attention. Though AUC is widely used to assess the accuracy of models (López-Ramírez et al. 2024; Kishore et al. 2024), this approach has drawbacks, since omission errors and behavioral errors are equally weighted (Lobo et al. 2008; Wei et al. 2024). A comprehensive analysis using multiple metrics such as the Kappa statistic (Kappa), the True Skills Statistic (TSS), and some new metrics should be considered in further research in the future (Somodi et al. 2024).

4.2 Variables contribution

Bio12 and aspect are the most indispensable variables for the distribution modeling of *Picea crassifolia* in Qilian Mountain Nature Reserve. The finding is consistent with many existing studies (Tu et al. 2022; Zhao et al. 2010). Soil moisture is the foundation of the ecosystem and the key to vegetation construction (Vereecken et al. 2022), as the climate of Qilian Mountain Nature Reserve is arid to semi-arid (Gou and Zhu 2021), it may be

primarily influenced by precipitation and additionally modulated by topography (Sehler et al. 2019; Du et al. 2022).

The contribution of topographic-related variables increased with finer data resolution, which highlights the importance of topographic data at high resolution (Scales et al. 2016). Owing to environmental heterogeneity and intraspecific interactions, the spatial distribution of *Picea crassifolia* is patchy within this study region (Kanagaraj et al. 2019; Du et al. 2021). The finer topography predictors may sufficiently depict the patchy environment characters. Therefore, the local microclimate was more affected by the local topographic than climate factors (Lembrechts 2023). When employing coarse data, climatic-related factors were pivotal determinants for tree distribution (Oliveira et al. 2021). Topography-related attributes such as elevation, slope, and aspect often demonstrated limited predictive capacity (Neilson 1995). However, at higher resolution, the influence of topographic variables is highlighted and is more useful for modeling the distribution of species habitat.

4.3 Changes of the potential distribution to the *Picea crassifolia*

Currently, the potential habits for *Picea crassifolia* were confirmed in the central and northern Qilian Mountains Nature Reserve, while the western region is unsuitable. These results consist with the fact that *Picea crassifolia* is the main tree species in this study area (Wang et al. 2019).

The results also showed that the distribution of *Picea crassifolia* will slightly increase under future scenarios, which agrees with previous studies (e.g., Xu et al. 2009). Specifically, *Picea crassifolia* is expected to gain in the eastern and lose in the central part of the Qilian Mountains Nature Reserve in the future. This change is attributable to the regional climate variability that is driven by westerlies and monsoons (Li et al. 2016). In general, *Picea crassifolia* performs well in Bio12 and Bio10, being 330-430 mm, and 9°~14°, respectively (Peng et al. 2014). Significant temperature and precipitation fluctuations in the central area under future scenarios, may be beyond the temperature threshold that is suitable for the *Picea crassifolia* (Xu et al. 2012).

4.4 Implications for *Picea crassifolia* management

Climatically suitable habits for *Picea crassifolia* in the study region are expected to expand in the future, which is good news for forest management. *Picea crassifolia* could be planted in regions that are likely to become climatically suitable in the future. Since our model predicted a western gain of *Picea crassifolia*, we propose priority establishment plantations in this region.

Further, the variation in *Picea crassifolia* habitats under different climates and topographic conditions is analyzed and shown in Fig. 6. Specifically, the gain in potential habitat of *Picea crassifolia* was most noticed in the elevation range of 2350-2700 and 3050-3400 m a.s.l., slopes range of 30°-45°, and northern (N) slopes. The loss in potential habitat was concentrated distribution in the elevation of 2000-2350 m a.s.l., slopes range of 45°-60°, and southern (S). The comparison of the increase and loss ratios of *Picea crassifolia* in different geographical regions can indicate its suitable planting zones in the future. For elevation, the habitats for *Picea crassifolia* may decrease at lower elevations but increase at higher elevations, with the highest gain in the elevation range of 3050-3400 m a.s.l. in the SSP585 scenario. The magnitude of suitable area reduction in the elevation of 2000-2350 m a.s.l. increased with the degree of climate change. For slope, the habitats gain mainly occurred in the slope range of 0°-45° and with a maximum gain in the slope of 15°-30°, while in the slope of 45°-60° changes divergent. For aspect, the *Picea crassifolia* would lose most of its potential habitat in the southern slopes (S), with a loss range of 0.63% ~1.2% under future scenarios. The gain in potential habitat is noticed in the northern (N), north-western (NW), and north-eastern (NE) slopes, particularly in the northern slopes, with a maximum gain over 1% under the scenario of SSP585. In conclusion, these results indicate that areas characterized by high elevation, gentle slopes, and shady slopes were more suitable for *Picea crassifolia* distribution, especially in the regions of high elevation

range of 3050-3400 m a.s.l., gentle slopes range of 15°-45°, and N slopes.

Further, the habitat fragmentation indices of current and future are shown in Fig. 7. They were the highest in SSP585, and the lowest in current. In 2080, the ED and PD of the species range may increase by 3.19% and 4.20% on average, respectively. This suggests that climate change would expand the habits of *Picea crassifolia* in a patchy way. Therefore, the natural fragmentation distribution should be considered (Littlefield et al. 2019). Still, the presented change patterns may inform assisted species translocation efforts by identifying suitable target locations (Wang et al. 2018).

In all, the spatial and temporal area changes of *Picea crassifolia* can help guide long-term range surveys to find undiscovered critical habitats, thereby protecting the health and stability of endemic species in the region and the ecosystem, assisting in management in the future. Additionally, the research methods and qualitative conclusions in our study may provide a reference or guidance for other studies on forest distribution in dryland mountains. However, further work in tree physiology, field investigations, and controlled experiments are required in this area, which can be crucial for us to understand and quantify the impacts of individual factors and their interactions on the spatial distribution of *Picea crassifolia* forests under a changing climate.

5 Conclusions

In this study, SDMs were used to discuss the effect of topographic resolution on modeling the distribution of *Picea crassifolia* in the Qilian Mountains Nature Reserve. The results revealed that models with high-resolution topographic data increased the accuracy of *Picea crassifolia* prediction and affected variable importance. Aspect, allowing the depiction of smaller *Picea crassifolia* patches, became the most momentous one at 30m data resolution, although Bio12 was the most vital factor at 90m data resolution. The distribution of *Picea crassifolia* was located in the central and eastern Qilian Mountains Nature Reserve and all expected to increase at different future scenarios, especially in the eastern region of elevation of 3050-3400 m a.s.l., slope of 15°-45°, and north slope. Based on these results, we advocate the importance of monitoring the distribution of *Picea crassifolia* at a fine spatial resolution to be able to offer targeted regions for its planting, management, and sustainable development.

Acknowledgements

We sincerely thank the editors and the anonymous reviewers for their insightful comments and constructive suggestions. This work was supported by the National Natural Science Foundation of China (No. 42071057).

Author Contribution

ZHANG Xiang: Investigation, Data curation, Formal analysis, Writing - original draft, Writing – review & editing. GAO Linlin: Conceptualization, Methodology, Writing – review & editing, Funding acquisition. LUO Yu: Investigation, Data curation. YUAN Yiyun: Data curation. MA Baolong: Investigation. GOU Xiaohua: Conceptualization, Supervision. DENG Yang: Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Ethics declarations

Availability of Data/Materials: The data underlying this article will be shared on reasonable request to the corresponding author.

Conflict of Interest: The authors declare no conflict of interest.

References

- Araújo MB, Peterson AT (2012) Uses and misuses of bioclimatic envelope modeling. *Ecology* 93(7): 1527-1539. <https://esajournals.onlinelibrary.wiley.com/doi/10.1890/11-1930.1>
- Austin MP, Van Niel KP (2011) Impact of landscape predictors on climate change modeling of species distributions: a case study with *Eucalyptus fastigata* in southern New South Wales, Australia. *J Biogeogr* 38(1): 9-19. <https://doi.org/10.1111/j.1365-2699.2010.02415.x>
- Bai B, Yue P, Zhang Q, et al. (2023) Changing characteristics of ecosystem and water storage under the background of warming and humidification in the Qilian Mountains, China. *Sci Total Environ* 893: 164959. <https://doi.org/10.1016/j.scitotenv.2023.164959>
- Booth TH, McMurtrie RE (1988) Climatic change and *Pinus radiata* plantations in Australia. CSIRO. pp 534-545. <https://ebooks.publish.csiro.au/content/greenhouse-planning-climate-change>
- Booth TH, Nix HA, Busby JR, et al. (2014) BIOCLIM: the first species distribution modeling package, its early applications and relevance to most current MaxEnt studies. *Divers Distrib* 20(1): 1-9. <https://doi.org/10.1111/ddi.12144>
- Booth TH (2018) Species distribution modeling tools and databases to assist managing forests under climate change. *For Ecol Manage* 430: 196-203. <https://doi.org/10.1016/j.foreco.2018.08.019>
- Booth TH (2024) Forestry trials and species adaptability to climate change. *Global Change Biol* 30(3): e17243. <https://doi.org/10.1111/gcb.17243>
- Bradley AP (1997) The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recogn* 30(7): 1145-1159. [https://doi.org/10.1016/S0031-3203\(96\)00142-2](https://doi.org/10.1016/S0031-3203(96)00142-2)
- Bramer I, Anderson BJ, Bennie J, et al. (2018) Advances in monitoring and modeling climate at ecologically relevant scales. *Adv Ecol Res* 58: 101-161. <https://doi.org/10.1016/bs.aecr.2017.12.005>
- Busby JR (1988) Potential implications of climate change on Australia's flora and fauna. CSIRO. pp 387-398. <https://ebooks.publish.csiro.au/content/greenhouse-planning-climate-change>
- Cao XP, Wang JR, Lu SS, et al. (2019) Simulation of the potential distribution patterns of *Picea crassifolia* in climate change scenarios based on the maximum entropy (Maxent) model. *Acta Ecol Sinica* 39(14): 5232-5240. (In Chinese) <https://doi.org/10.5846/stxb201809151999>
- Chang XX, Zhao WZ, Liu H, et al. (2014) Qinghai spruce (*Picea crassifolia*) forest transpiration and canopy conductance in the upper Heihe River Basin of arid northwestern China. *Agr Forest Meteorol* 198-199: 209-220. <https://doi.org/10.1016/j.agrformet.2014.08.015>
- Chauvier Y, Descombes P, Guéguen M, et al. (2022) Resolution in species distribution models shapes spatial patterns of plant multifaceted diversity. *Ecography* 2022(10): e05973. <https://doi.org/10.1111/ecog.05973>
- Chhogyel N, Kumar L, Bajgai Y, et al. (2020) Prediction of Bhutan's ecological distribution of rice (*Oryza sativa* L.) under the impact of climate change through maximum entropy modelling. *J Agricul Sci* 158(1-2): 25-37. <https://doi.org/10.1017/S0021859620000350>
- Coumou D, Rahmstorf S (2012) A decade of weather extremes. *Nat Clim Change* 2: 491-496. <https://doi.org/10.1038/nclimate1452>
- Diffenbaugh NS, Singh D, Mankin JS (2018) Unprecedented climate events: Historical changes, aspirational targets, and national commitments. *Sci Adv* 4: eaao3354. <https://doi.org/10.1126/sciadv.aao3354>
- Dobrowski SZ (2011) A climatic basis for microrefugia: the influence of terrain on climate. *Global Change Biol* 17(2): 1022-1035. <https://doi.org/10.1111/j.1365-2486.2010.02263.x>
- Du J, Wang W, He ZB, et al. (2021) Spatial variability of phenological phenotype of *Picea crassifolia* in Qilian Mountains and its internal mechanism. *Chin J Plant Ecol* 45(8): 834-843. <https://doi.org/10.17521/cjpe.2021.0100>
- Du QQ, Sun YF, Guan QY, et al. (2022) Vulnerability of grassland ecosystems to climate change in the Qilian Mountains, northwest China. *J Hydrol* 612: 128305. <https://doi.org/10.1016/j.jhydrol.2022.128305>
- Ehrlén J, Morris WF (2015) Predicting changes in the distribution and abundance of species under environmental change. *Ecol Lett* 18(3): 303-314.

- <https://doi.org/10.1111/ele.12410>
- Elith J, Phillips SJ, Hastie T, et al. (2010) A statistical explanation of MaxEnt for ecologists. *Divers Distrib* 17(1): 43-57. <https://doi.org/10.1111/j.1472-4642.2010.00725.x>
- Elith J, Leathwick JR (2009) Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annu Rev Ecol Evol S* 40: 677-697. <https://doi.org/10.1146/annurev.ecolsys.110308.120159>
- Feng S, Xi EN, Wan W, et al. (2023) Genomic signals of local adaptation in *Picea crassifolia*. *Bmc Plant Biol* 23: 534. <https://doi.org/10.1186/s12870-023-04539-7>
- Fiore S, Elia D, Blanquer I, et al. (2017) BioClimate: A Science Gateway for Climate Change and Biodiversity research in the EUBrazilCloudConnect project. *Future Gener Comp Sy* 94: 895-909. <https://doi.org/10.1016/j.future.2017.11.034>
- Gou QP, Zhu QK (2021) Response of deep soil moisture to different vegetation types in the Loess Plateau of northern Shannxi, China. *Sci Rep* 11: 15098. <https://doi.org/10.1038/s41598-021-94758-5>
- Guisan A, Thuiller W, Zimmermann NE (2017) *Habitat Suitability and Distribution Models: with Applications in R*. Cambridge Univ Press. <https://doi.org/10.1017/9781139028271>
- Guisan A, Zimmermann NE (2000) Predictive habitat distribution models in ecology. *Ecol Model* 135(2-3): 147-186. [https://doi.org/10.1016/S0304-3800\(00\)00354-9](https://doi.org/10.1016/S0304-3800(00)00354-9)
- Hannah L, Flint L, Syphard AD, et al. (2014) Fine-grain modeling of species' response to climate change: holdouts, stepping-stones and microrefugia. *Trends Ecol Evol* 29(7): 390-397. <https://doi.org/10.1016/j.tree.2014.04.006>
- Hijmans RJ, Cameron SE, Parra JL, et al. (2005) Very high resolution interpolated climate surfaces for global land areas. *Int J Climatol* 25(15): 1965-1978
- Jie Y, Xin H (2022) The 30 m annual land cover datasets and its dynamics in China from 1990 to 2021 [Data set]. *Earth Syst Sci Data* 13(8): 3907-3925. <https://doi.org/10.5194/essd-13-3907-2021>
- Kanagaraj R, Araujo MB, Barman R, et al. (2019) Predicting range shifts of Asian elephants under global change. *Divers Distrib* 25(5): 822-838. <https://doi.org/10.1111/ddi.12898>
- Kishore BSPC, Kumar A, Saikia P (2024) Understanding the invasion potential of *Chromolaena odorata* and *Lantana camara* in the Western Ghats, India: An ecological niche modeling approach under current and future climatic scenarios. *Ecol Inform* 79: 102425. <https://doi.org/10.1016/j.ecoinf.2023.102425>
- Lembrechts JJ (2023) Microclimate alters the picture. *Nat Clim Change* 13: 423-424. <https://doi.org/10.1038/s41558-023-01632-5>
- Lenoir J, Hattab T, Pierre G (2016) Climatic microrefugia under anthropogenic climate change: implications for species redistribution. *Ecography* 40(2): 253-266. <https://doi.org/10.1111/ecog.02788>
- Li Y, Zhang CQ, Wang Y (2016) The verification of millennial-scale monsoon water vapor transport channel in northwest China. *J Hydrol* 536: 273-283. <https://doi.org/10.1016/j.jhydrol.2016.03.006>
- Liang PB, Li ZQ, Zhang H (2019) Temporal-spatial variation characteristics of snow cover in Qilian Mountains from 2001 to 2017. *Arid Land Geography* 42(1): 56-66. <https://doi.org/10.12118/j.issn.1000-6060.2019.01.07>
- Littlefield CE, Krosby M, Michalak JL, et al. (2019) Connectivity for species on the move: supporting climate-driven range shifts. *Front Ecol Environ* 17(5): 270-278. <https://doi.org/10.1002/fee.2043>
- Liu C, Berry PM, Dawson TP, et al. (2005) Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* 28(3): 385-393. <https://doi.org/10.1111/j.0906-7590.2005.03957.x>
- Lobo JM, Jiménez-Valverde A, Real R (2008) AUC: a misleading measure of the performance of predictive distribution models. *Global Ecol Biogeogr* 17(2): 145-151. <https://doi.org/10.1111/j.1466-8238.2007.00358.x>
- López-Ramírez S, Márquez AL, Real R, et al. (2024) Evaluating the expansion of African species into Europe driven by climate change. *Divers Distrib* 30(6): e13840. <https://doi.org/10.1111/ddi.13840>
- Maclean IMD, Early R (2023) Macroclimate data overestimate range shifts of plants in response to climate change. *Nat Clim Change* 13: 484-490.

- <https://doi.org/10.1038/s41558-023-01650-3>
- Mahmoodi S, Ahmadi K, Heydari M, et al. (2023) Elevational shift of endangered European yew under climate change in Hyrcanian mountain forests: Rethinking conservation-restoration strategies and management. *Forest Ecol Manag* 529: 120693. <https://doi.org/10.1016/j.foreco.2022.120693>
- Makowski D, Ben-Shachar MS, Patil I, et al. (2020) Methods and algorithms for correlation analysis in R. *Journal of Open Source Software* 5(51): 2306. <https://doi.org/10.21105/joss.02306>
- Meineri E, Hylander K (2017) Fine-grain, large-domain climate models based on climate station and comprehensive topographic information improve microrefugia detection. *Ecography* 40(8): 1003-1013. <https://doi.org/10.1111/ecog.02494>
- Neilson RP (1995) A Model for Predicting Continental-Scale Vegetation Distribution and Water Balance. *Ecol Appl* 5(2): 362-385. <https://doi.org/10.2307/1942028>
- Murphy SJ, Smith AB (2021) What can community ecologists learn from species distribution models? *Ecosphere* 12(12): e03864. <https://doi.org/10.1002/ecs2.3864>
- Oliveira GDC, Arruda DM, Filho EIF, et al. (2021) Soil predictors are crucial for modeling vegetation distribution and its responses to climate change. *Sci Total Environ* 780: 146680. <https://doi.org/10.1016/j.scitotenv.2021.146680>
- Peng S, Zhao C, Xu Z, et al. (2014) Restoration and conservation potential of destroyed Qinghai spruce (*Picea crassifolia*) forests in the Qilian Mountains of northwest China. *Mitig Adapt Strat Gl* 21: 153-165. <https://doi.org/10.1007/s11027-014-9581-4>
- Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. *Ecol Model* 190(3-4): 231-259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Puchałka R, Paż-Dyderska S, Dylewski Ł, et al. (2023) Forest herb species with similar European geographic ranges may respond differently to climate change. *Sci Total Environ* 905: 167303. <https://doi.org/10.1016/j.scitotenv.2023.167303>
- Randin CF, Engler R, Normand S, et al. (2009) Climate change and plant distribution: local models predict high-elevation persistence. *Glob Change Biol* 15(6): 1557-1569. <https://doi.org/10.1111/j.1365-2486.2008.01766.x>
- Scales KL, Hazen EL, Jacox MG, et al. (2016) Scale of inference: on the sensitivity of habitat models for wide-ranging marine predators to the resolution of environmental data. *Ecography* 40(1): 210-220. <https://doi.org/10.1111/ecog.02272>
- Sehler R, Li J, Reager J (2019) Investigating Relationship Between Soil Moisture and Precipitation Globally Using Remote Sensing Observations. *J Contemp Wat Res Ed* 168: 106-118. <https://doi.org/10.1111/j.1936-704x.2019.03324.x>
- Somodi I, Bede-Fazekas Á, Botta-Dukát Z, et al. (2024) Confidence and consistency in discrimination: A new family of evaluation metrics for potential distribution models. *Ecol Model* 491: 10667. <https://doi.org/10.1016/j.ecolmodel.2024.110667>
- Stoklosa J, Daly C, Foster SD, et al. (2014) A climate of uncertainty: accounting for error in climate variables for species distribution models. *Methods Ecol Evol* 6(4): 412-423. <https://doi.org/10.1111/2041-210X.12217>
- Swets JA (1998) Measuring the Accuracy of Diagnostic Systems. *Science* 240: 1280-1293. <https://doi.org/10.1126/science.3287615>
- Schmitt S, Pouteau R, Justeau D, et al. (2017) ssdm: An R package to predict distribution of species richness and composition based on stacked species distribution models. *Methods Ecol Evol* 8(12): 1795-1803. <https://doi.org/10.1111/2041-210X.12841>
- Thackeray SJ, Henrys PA, Hemming D, et al. (2016) Phenological sensitivity to climate across taxa and trophic levels. *Nature* 535: 241-245. <https://doi.org/10.1038/nature18608>
- Tu ZY, Gou XH, Zou SB (2022) Potential distribution of *Picea crassifolia* on the northern slope of Qilian Mountains. *Journal of Nanjing Forestry University(Natural Science Edition)* 46(2): 221-226. (in Chinese) <https://doi.org/10.12302/j.issn.1000-2006.202012011>
- Vereecken H, Amelung W, Bauke SL, et al. (2022) Soil hydrology in the Earth system. *Nat Rev Earth Env* 3: 573-587. <https://doi.org/10.1038/s43017-022-00324-6>
- Waldock C, Stuart-Smith RD, Albouy C, et al. (2022) A quantitative review of abundance-based species distribution models. *Ecosphere* 2022(1). <https://doi.org/10.1111/ecog.05694>
- Wang L, Chen RS, Han CT, et al. (2019) Change characteristics of precipitation and temperature in the Qilian Mountains and Hexi Oasis, Northwestern

- China. Environ Earth Sci, 78: 284.
<https://doi.org/10.1007/s12665-019-8289-x>
- Wang XL, Blanchet FG, Koper N. (2014) Measuring habitat fragmentation: An evaluation of landscape pattern metrics. Methods Ecol Evol 5(7): 634-646.
<https://doi.org/10.1111/2041-210X.12198>
- Wang ZY, Liu XH, Peñuelas J, et al. (2023) Recent shift from dominant nitrogen to CO₂ fertilization control on the growth of mature Qinghai spruce in China's Qilian Mountains. Agric For Meteorol 343: 109779. <https://doi.org/10.1016/j.agrformet.2023.109779>
- Wei JF, Niu MM, Zhang HX, et al. (2024) Global Potential Distribution of Invasive Species *Pseudococcus viburni* (Hemiptera: Pseudococcidae) under Climate Change. Insect 15(3): 195.
<https://doi.org/10.1016/j.agrformet.2023.109779>
- Xu ZL, Zhao CY, Feng ZD. (2009) A study of the impact of climate change on the potential distribution of Qinghai spruce (*Picea crassifolia*) in Qilian Mountains. Acta Ecol Sinica 29(5): 278-285.
<https://doi.org/10.1016/j.chnaes.2009.09.004>
- Xu ZL (2011) Species potential distribution models and evaluation based on dissimilarity index of variables of Qinghai spruce (*Picea crassifolia*) in Qilian mountains. Journal of Lanzhou University.
<https://api.semanticscholar.org/CorpusID:130899529>
- Xu ZL, Zhao CY, Zhao DF, et al. (2012) Estimating realized and potential carbon storage benefits from reforestation and afforestation under climate change: A case study of the Qinghai spruce forests in the Qilian Mountains northwestern China. Mitig Adapt Strateg Glob Chang 18: 1257-1268.
<https://doi.org/10.1007/s11027-012-9420-4>
- Yang JL, Dong JW, Xiao XM, et al. (2019) Divergent shifts in peak photosynthesis timing of temperate and alpine grasslands in China. Remote Sens Environ 233: 111395.
<https://doi.org/10.1016/j.rse.2019.111395>
- Zhao CY, Bie Q, Peng HH. (2010) Analysis of the Niche Space of *Picea crassifolia* on the Northern Slope of Qilian Mountains. Acta Ecologica Sinica 65: 113 - 121. (in Chinese)
- Zhang YX, Shao XM, Wilmking M. (2011) Dynamic relationships between *Picea crassifolia* growth and climate at upper treeline in the Qilian Mts., Northeast Tibetan Plateau, China. Dendrochronologia 29(4): 185-199. <https://doi.org/10.1016/j.dendro.2010.11.001>
- Zuo YF, Li YH, He KN, et al. (2022) Temporal and spatial variation characteristics of vegetation coverage and quantitative analysis of its potential driving forces in the Qilian Mountains, China, 2000-2020. Ecol Indic 143: 109429. <https://doi.org/10.1016/j.ecolind.2022.109429>

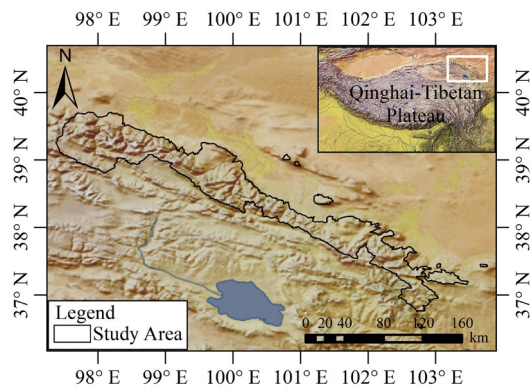


Fig. 1 Location of the Qilian Mountains Nature Reserve.

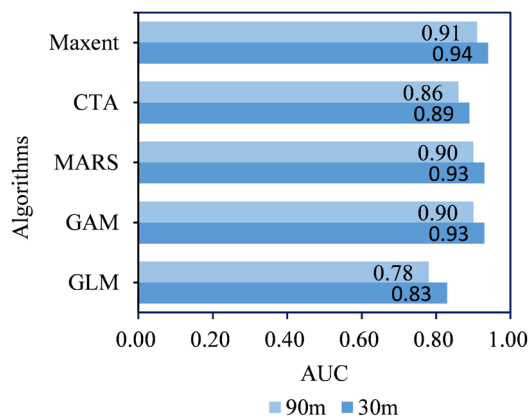


Fig. 2 Area under the receiver operating characteristic curve (AUC) to assess the representation of species distribution models (SDMs) with different modeling techniques and resolutions in simulating the spatial distribution of *Picea crassifolia* in the Qilian Mountains Nature Reserve. GLM: Generalized linear model; GAM: Generalized additive model; MARS: Multivariate adaptive regression spline; CTA: Classification tree; MaxEnt: Maximum entropy; AUC: The area under the receiver operating characteristic curve.

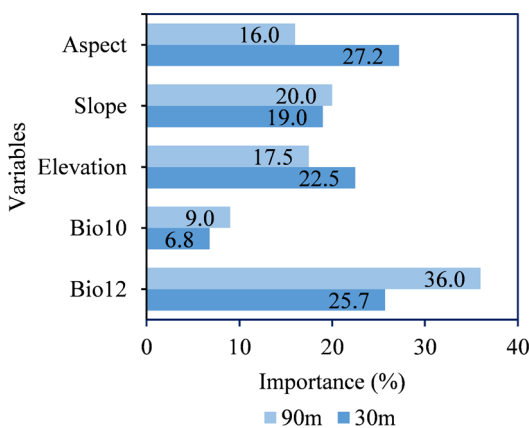


Fig. 3 Importance (%) of the climate and topography variables in the ensemble models at two different resolutions. Bio10: Mean temperature of warmest quarter; Bio12: Annual precipitation.

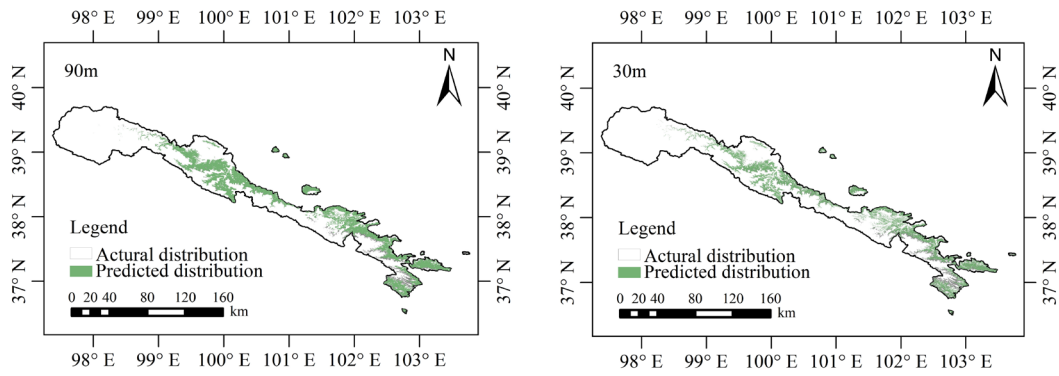


Fig. 4 Current (1970–2000) potential distribution of *Picea crassifolia* in 90m and 30m MaxEnt models.

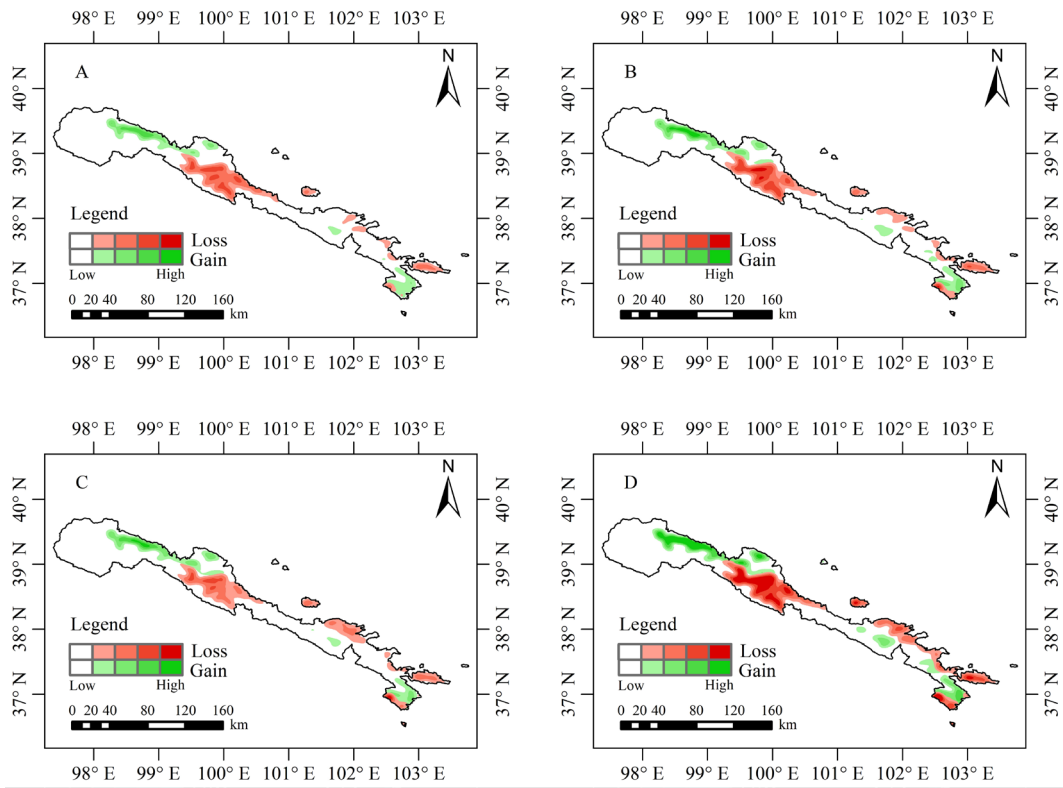
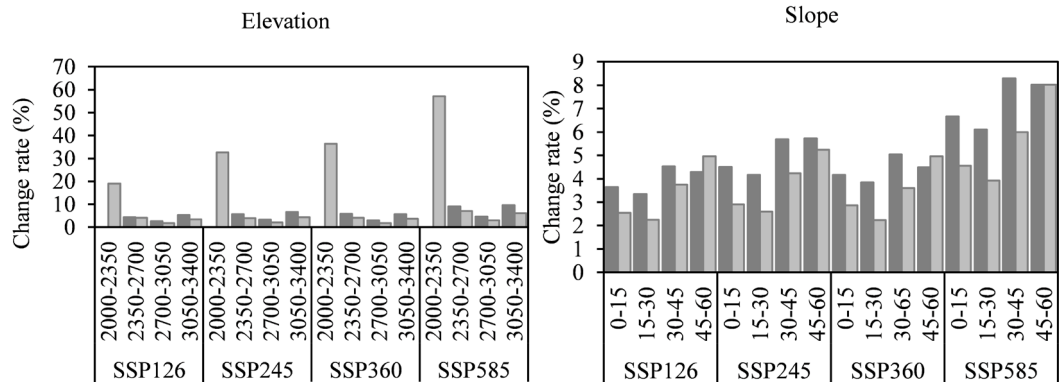


Fig. 5 Spatial loss and gain regions of distribution area for *Picea crassifolia* growth under future scenarios, obtained by kernel density analysis. (A) SSP126; (B) SSP245; (C) SSP370; (D) SSP585.



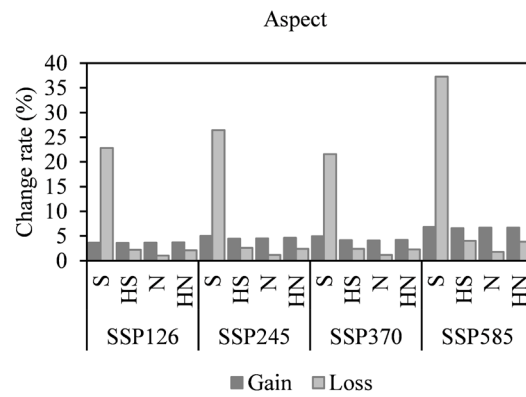


Fig. 6 Rate of gain and loss of *Picea crassifolia* habitats in different topography ranges under future scenarios, compared with the habitats under current conditions.

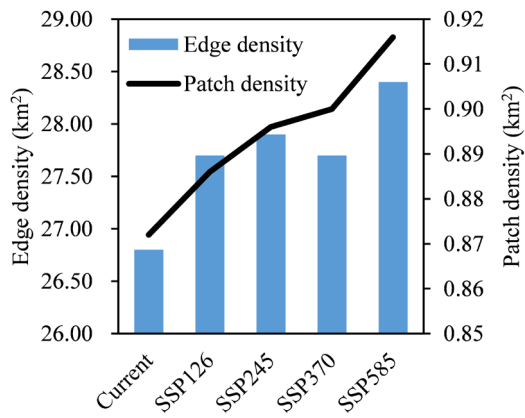


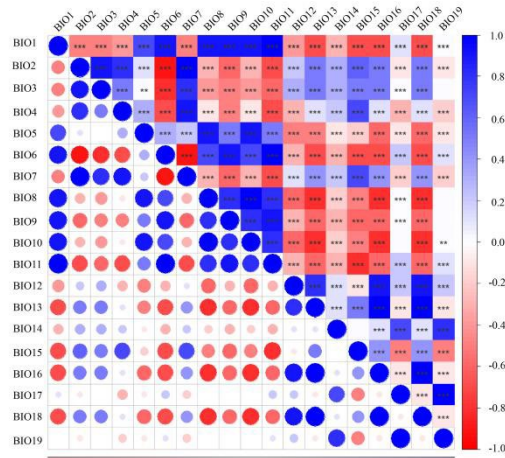
Fig. 7 Disparity in habitat fragmentation indices across various scenarios.

Table 1 Statistics of the habitat changes (km²) in the four suitable classes for *Picea crassifolia* distribution under the SSP126, SSP245, SSP370, SSP585 scenarios. Change of suitable area: Divide the future suitable area change by the current suitable area (the sum of the poorly suitable area, moderately suitable area, and highly suitable area, about 5110.65 km²).

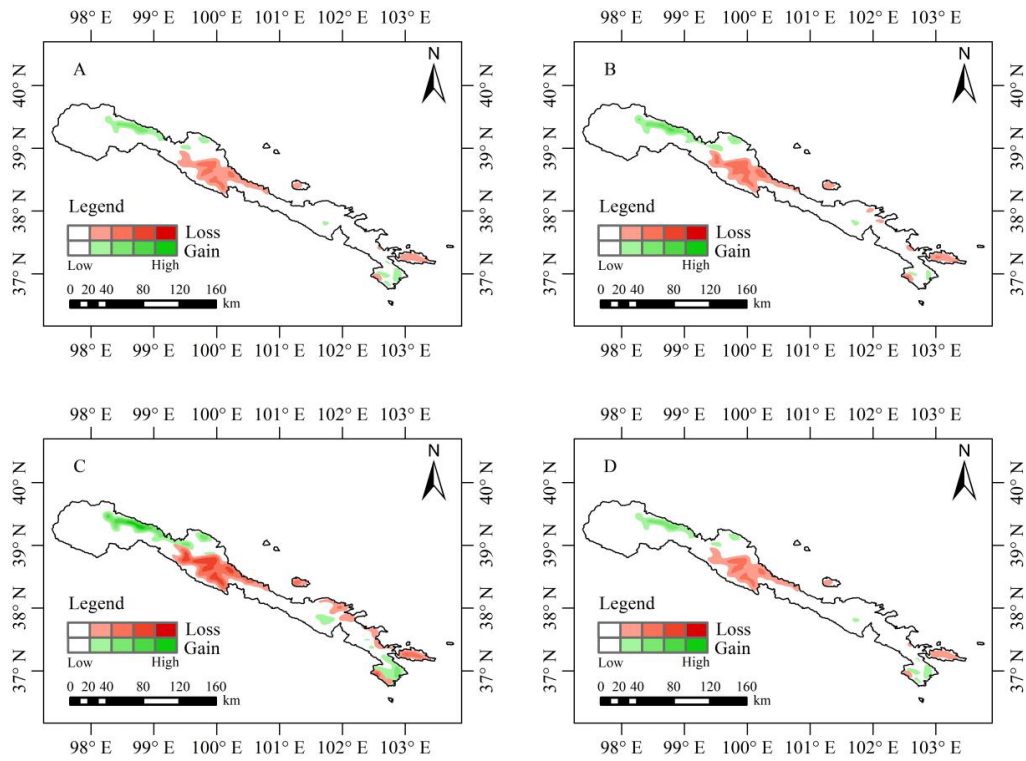
| | Future scenarios | | | |
|---|------------------|--------|--------|---------|
| | SSP126 | SSP245 | SSP370 | SSP585 |
| Unsuitable area (km ²) | -52.25 | -79.18 | -74.70 | -110.16 |
| Poorly suitable area (km ²) | -6.57 | 1.30 | 7.70 | -5.08 |
| Moderately suitable area (km ²) | 21.62 | 31.20 | 21.98 | 50.03 |
| Highly suitable area (km ²) | 37.19 | 46.69 | 45.02 | 65.21 |
| Change of suitable area | 0.01 | 0.02 | 0.01 | 0.02 |

Table 2 Transition of *Picea crassifolia* habitats (km²) in suitability classes across different periods. (Unit: km²)

| | | Current (1970–2000) | | | |
|-----------------|--------------------------|---------------------|----------------------|--------------------------|----------------------|
| | | Unsuitable area | Poorly suitable area | Moderately suitable area | Highly suitable area |
| SSP126 scenario | Unsuitable area | 0.990 | 0.064 | | |
| | Poorly suitable area | 0.010 | 0.881 | 0.054 | |
| | Moderately suitable area | | 0.054 | 0.899 | 0.061 |
| | Highly suitable area | | | 0.047 | 0.938 |
| SSP245 scenario | Unsuitable area | 0.988 | 0.071 | | |
| | Poorly suitable area | 0.012 | 0.864 | 0.059 | |
| | Moderately suitable area | | 0.065 | 0.884 | 0.070 |
| | Highly suitable area | | | 0.056 | 0.929 |
| SSP370 scenario | Unsuitable area | 0.990 | 0.066 | | |
| | Poorly suitable area | 0.011 | 0.876 | 0.055 | |
| | Moderately suitable area | | 0.058 | 0.892 | 0.063 |
| | Highly suitable area | | | 0.052 | 0.937 |
| SSP585 scenario | Unsuitable area | 0.983 | 0.100 | | |
| | Poorly suitable area | 0.017 | 0.806 | 0.084 | 0.001 |
| | Moderately suitable area | | 0.093 | 0.834 | 0.107 |
| | Highly suitable area | | | 0.081 | 0.892 |



Appendix 1 Correlation coefficients of 19 bio-climate variables. $P < 0.001$, ***; $P < 0.05$, **; $P < 0.01$, *.



Appendix 2 Spatial loss and gain regions of distribution area for *Picea crassifolia* growth under future scenarios, obtained by kernel density analysis. (A) SSP126, (B) SSP245, (C) SSP370, (D) SSP585 of 2021-2040.

Appendix3 Statistics of the habitat changes in the four suitable classes for *Picea crassifolia* distribution under the SSP126, SSP245, SSP370, SSP585 scenarios of 2021-2040. Change of suitable area: Current suitable area divides by the future change area.

| | Current | Future scenarios | | | |
|---|----------|------------------|--------|--------|--------|
| | | SSP126 | SSP245 | SSP370 | SSP585 |
| Unsuitable area (km ²) | 21798.77 | -37.57 | -38.85 | -64.30 | -56.44 |
| Poorly suitable area (km ²) | 2752.40 | -6.54 | -2.76 | -6.06 | -1.34 |
| Moderately suitable area (km ²) | 1703.88 | 14.88 | 14.24 | 28.29 | 20.74 |
| Highly suitable area (km ²) | 710.81 | 29.22 | 27.37 | 42.06 | 37.05 |
| Change of suitable area (%) | / | 0.01 | 0.01 | 0.01 | 0.02 |

Appendix4 Transition of *Picea crassifolia* habitats in suitability classes across different periods of 2021-2040. (Unit: km²)

| | | Unsuitable area | Poorly suitable area | Moderately suitable area | Highly suitable area |
|-----------------|--------------------------|-----------------|----------------------|--------------------------|----------------------|
| SSP126 scenario | Unsuitable area | 0.994 | 0.006 | | |
| | Poorly suitable area | 0.034 | 0.932 | 0.034 | |
| | Moderately suitable area | | 0.029 | 0.940 | 0.031 |
| | Highly suitable area | | | 0.035 | 0.965 |
| SSP245 scenario | Unsuitable area | 0.994 | 0.006 | | |
| | Poorly suitable area | 0.037 | 0.928 | 0.035 | |
| | Moderately suitable area | | 0.032 | 0.936 | 0.032 |
| | Highly suitable area | | | 0.039 | 0.961 |
| SSP370 scenario | Unsuitable area | 0.990 | 0.010 | | |
| | Poorly suitable area | 0.055 | 0.892 | 0.053 | |
| | Moderately suitable area | | 0.046 | 0.906 | 0.048 |
| | Highly suitable area | | | 0.057 | 0.943 |
| SSP585 scenario | Unsuitable area | 0.992 | 0.008 | | |
| | Poorly suitable area | 0.045 | 0.911 | 0.044 | |
| | Moderately suitable area | | 0.037 | 0.923 | 0.040 |
| | Highly suitable area | | | 0.044 | 0.956 |